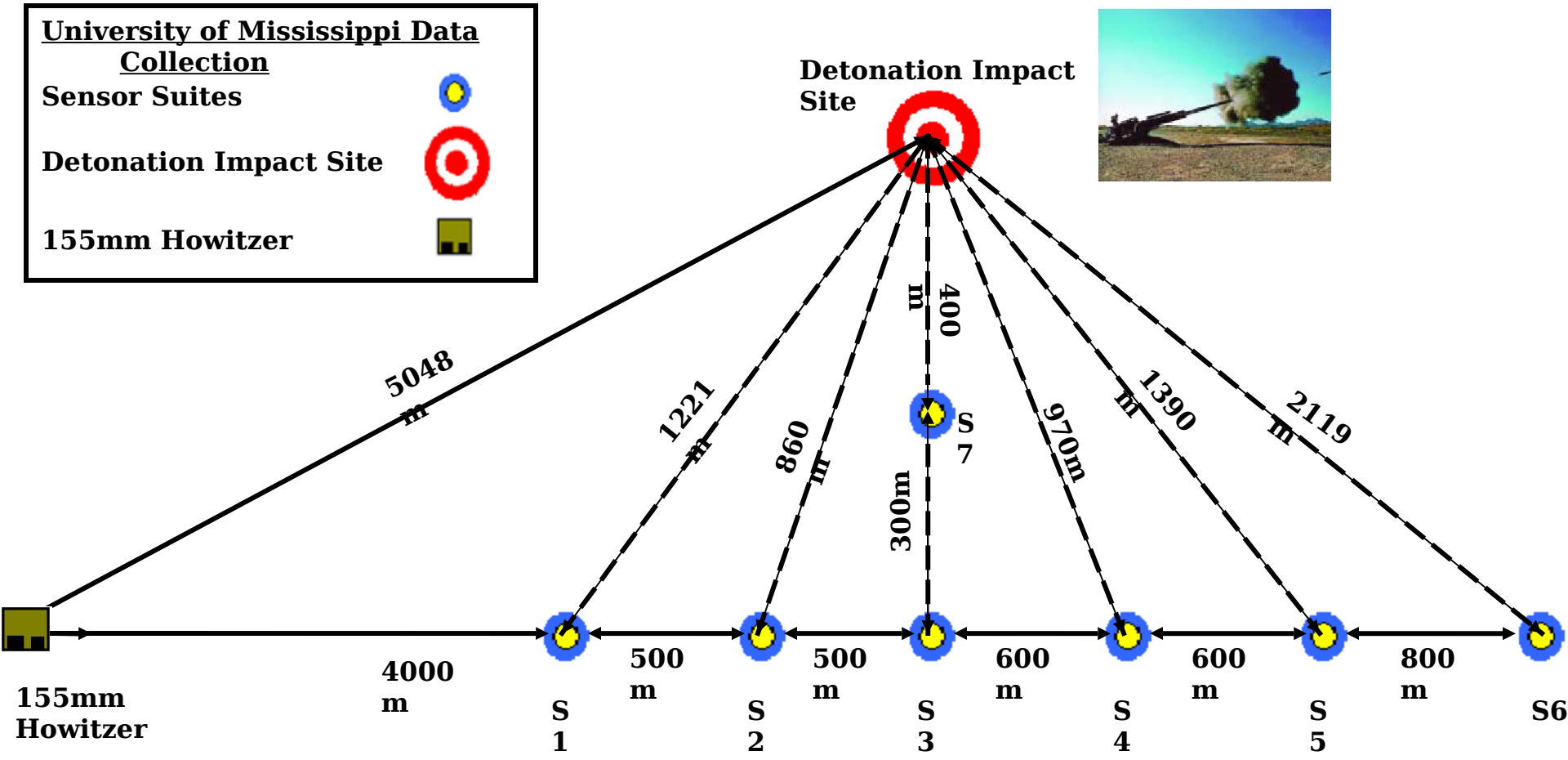
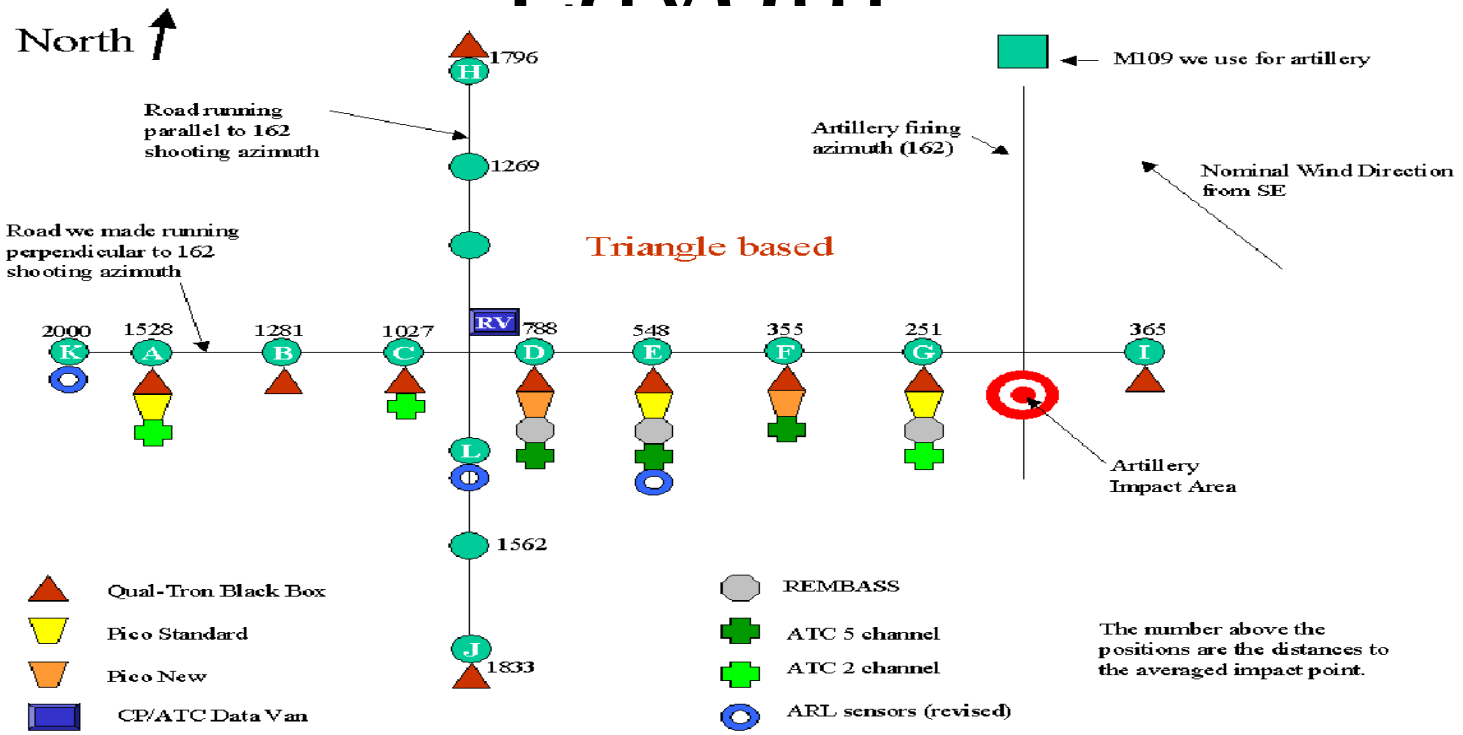
Discrimination between High Explosive and Potentially Chemical/Biological Artillery Using Acoustic Sensors

US Army RDECOM-ARDEC
By: Myron E. Hohil
Sachi Desai

Yuma Proving Ground (YPG) Test Layout



Disparate Sensor Integration (DSI) Test Layout

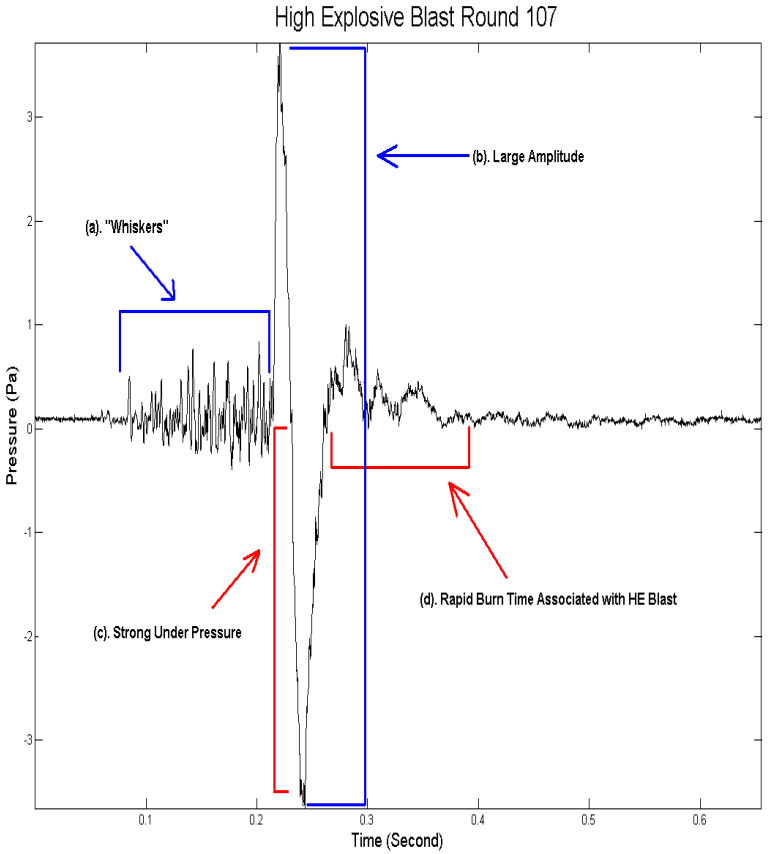


Acoustic Signature Data Collection of Blast Events

- Yuma Proving Ground Data Collection.
  - Conducted by National Center of Physical Acoustics (NCPA) in cooperation with ARDEC.
  - 39, 155mm rounds fired.
  - 3 categories of 155mm rounds were used, M107 HE, M110 CB, and M825 WP.
- Disparate Sensor Integration Data Collection.
  - Conducted by DSI Team and U.S. Army Edgewood Chemical Biological Center (ECBC) .
  - 265, 155mm rounds fired.
  - 2 categories of 155mm rounds were used, M107 HE and M110 CB

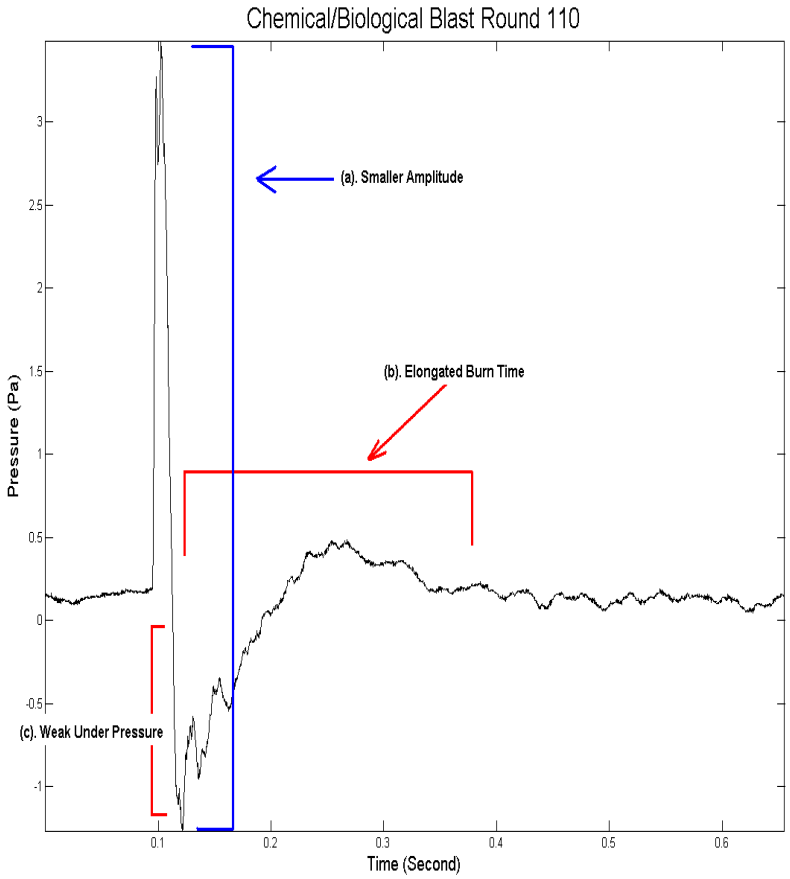
Typical Blast of M107 HE Round

- High frequency precursors to the main blast.
  - Generated by Supersonic Shrapnel Elements
- Large Amplitude of Main Blast.
- Large under pressure element .
  - Generated by 15lbs of explosives rapidly burning.
- Short Duration Signatures.



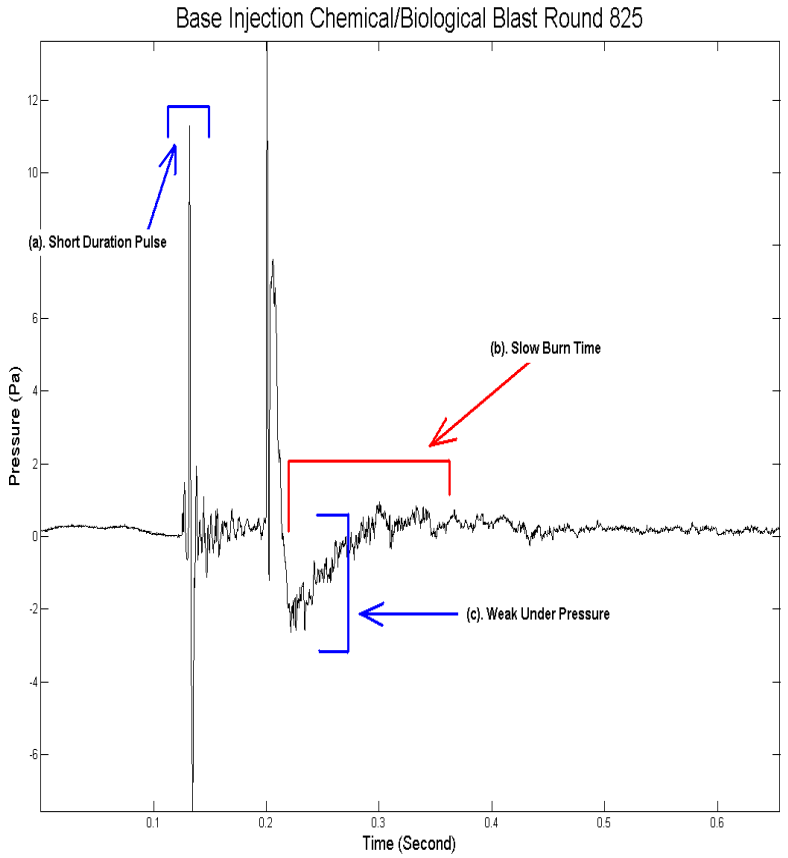
Typical Blast of M110 Simulated CB Round

- Small amplitude associated with main blast.
  - The explosive material being 2lbs.
- Elongated burn time following main blast.
  - The deliberately slow to properly release the compounds.
- Weak under pressure.



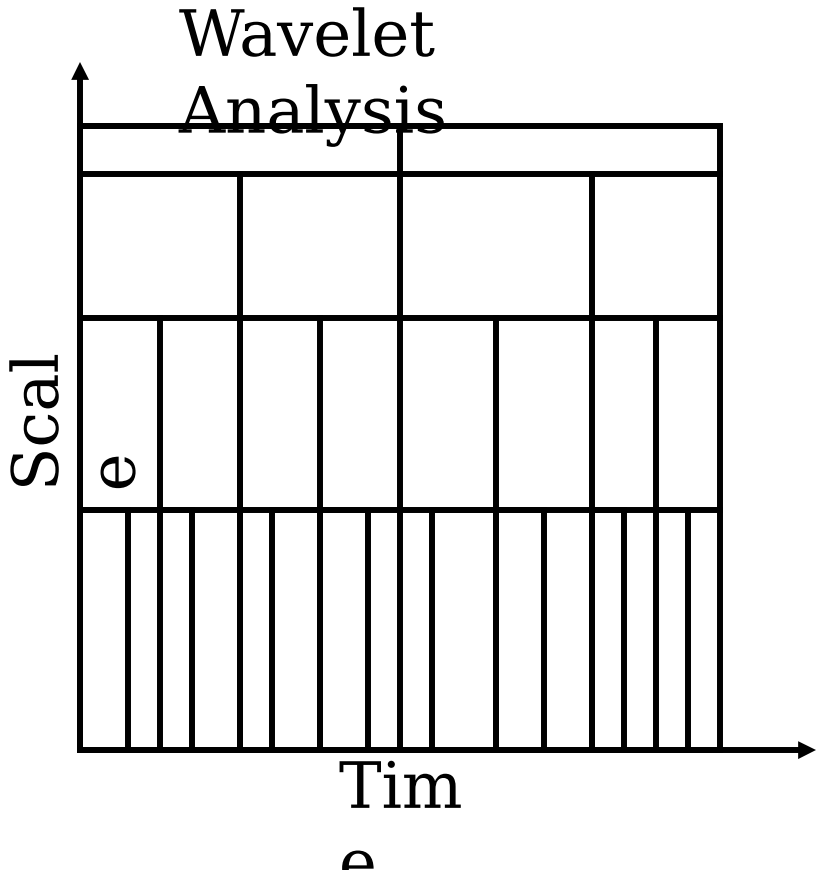
Typical Blast of WP825 Round

- Short Duration Pulse
  - Resulting from base ejection rounds.
- Weak Under Pressure
  - Small amount of Explosives.
- Slow Burn Time
  - Elongated to properly discharge contents of the round.



Wavelets

- Efficiently represent non-stationary, transient, and oscillatory signals.
- Desirable localization properties in both time and frequency that has appropriate decay in both properties.
- Provide a scalable time-frequency representation of artillery blast signature.



Discrete Wavelet Transform (DWT)

- Derived from subband filters and multiresolution decomposition.
  - Coarser Approximation.
  - Removing high frequency detail at each level of decomposition.
- Acts like a multiresolution transform.
  - Maps low frequency approximation in coarse subspace high frequency elements in a separate subspace.

Defining Parameters

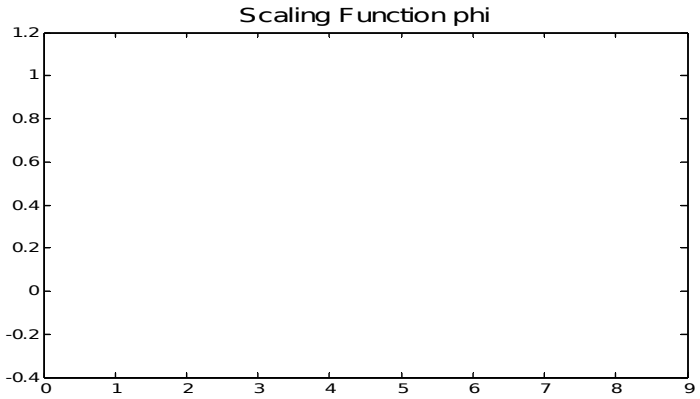
Scaling Function

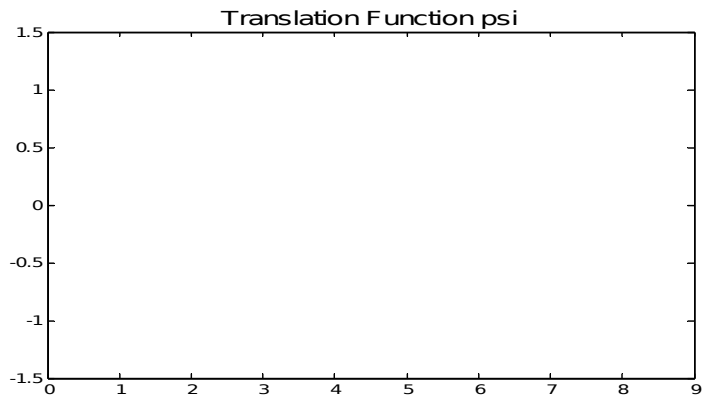
$$\varphi(x) = 2^{1/2} \sum_{k=0}^{L-1} h_{k+1} \varphi(2x - k)$$

Wavelet Function

$$\psi(x) = 2^{1/2} \sum_{k=0}^{L-1} g_{k+1} \varphi(2x - k)$$

Daubechies Wavelet n = 5

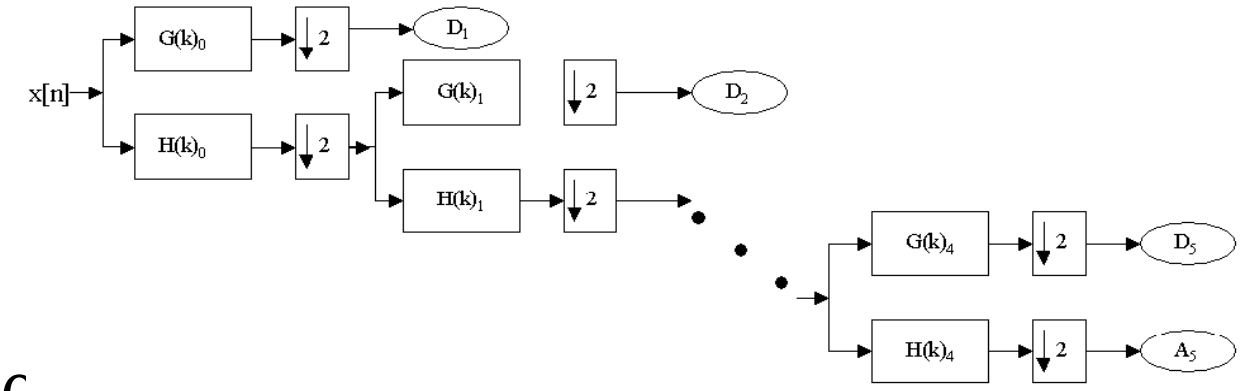




- Representation of the scaling and translation function of db5.
  - Scaling function resembles blast signature of M107 and M110 round.
  - Provides the ability to approximate signal with the characteristic wavelet.

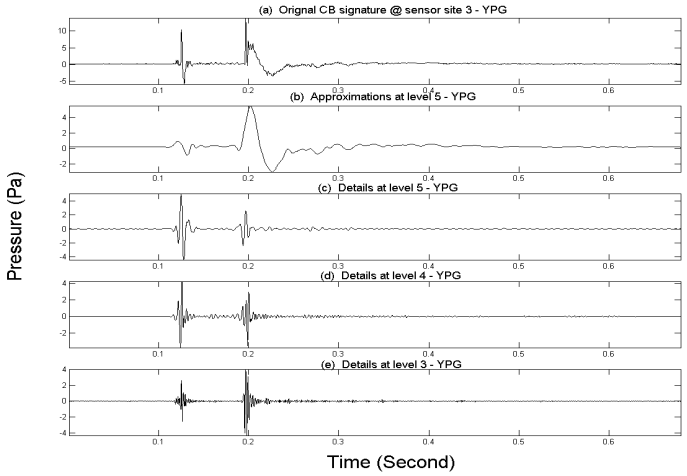
Multiresolutional Analysis

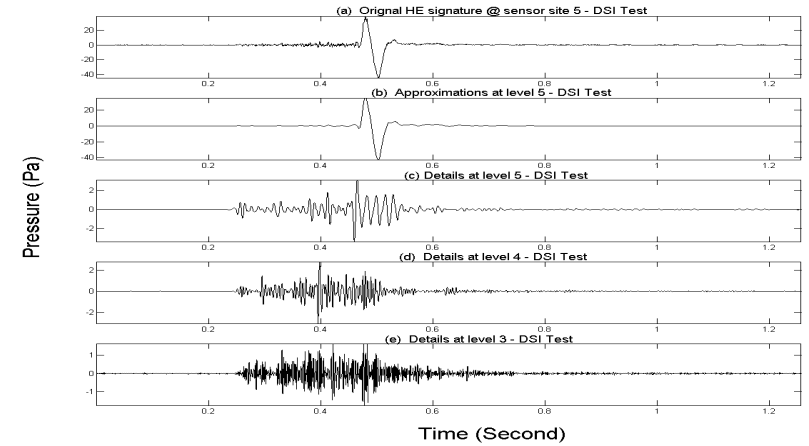
- Using a series of successive high pass and low pass filters to create a set of subspaces.
  - High pass filter obtains the details of the signatures while the low pass filter obtains a coarse approximation of the signal.
- The resulting banks of dyadic multirate filters separate the frequency components into different subbands.
  - Each pass through gives you resolution of factor 2.

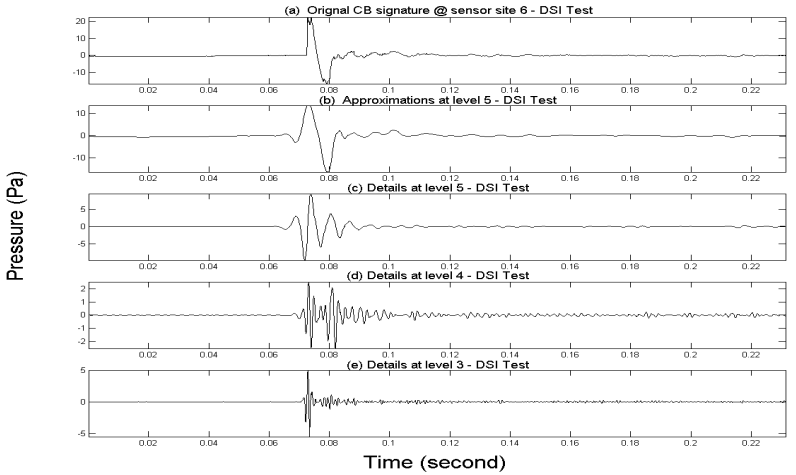


Effects of Wavelet Decomposition

- Wavelet decomposition to level 5 of three varying blast types from varying ranges.


(a) Orignal CB signature @ sensor site 3 - YPG
(b) Approximations at level 5 - YPG
(c) Details at level 5 - YPG
(d) Details at level 4 - YPG
(e) Details at level 3 - YPG
Pressure (Pa)
Time (Second)

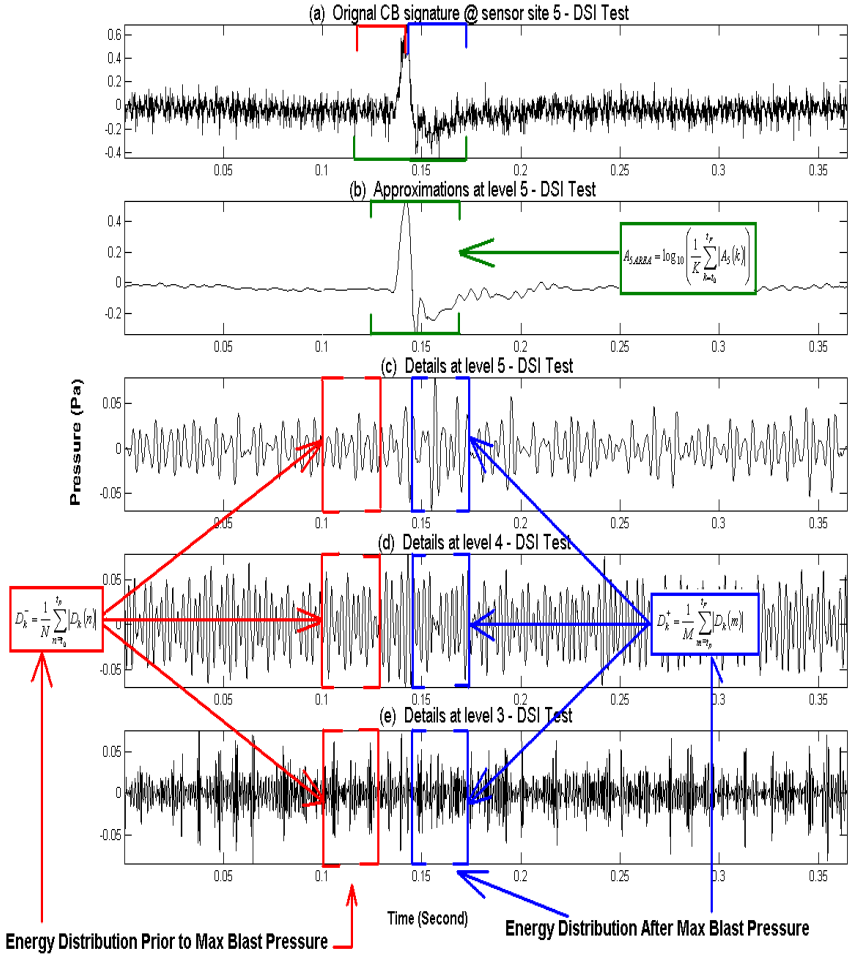

(a) Orignal HE signature @ sensor site 5 - DSI Test
(b) Approximations at level 5 - DSI Test
(c) Details at level 5 - DSI Test
(d) Details at level 4 - DSI Test
(e) Details at level 3 - DSI Test
Pressure (Pa)
Time (Second)

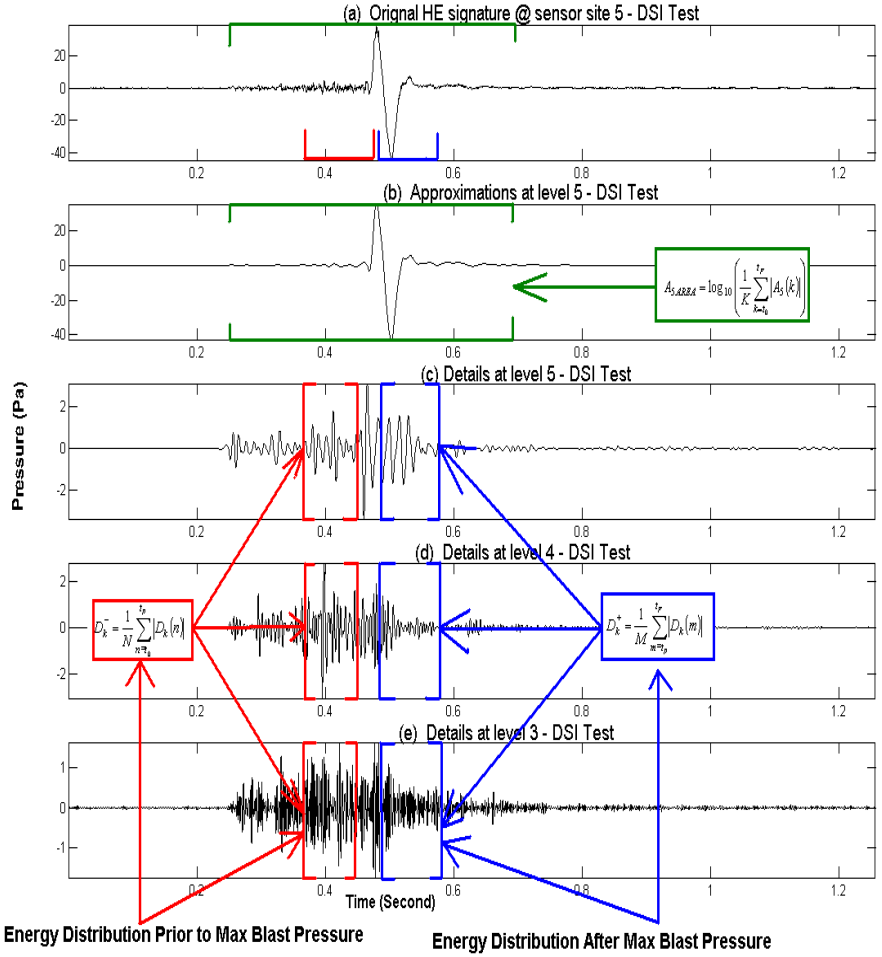

(a) Orignal CB signature @ sensor site 6 - DSI Test
(b) Approximations at level 5 - DSI Test
(c) Details at level 5 - DSI Test
(d) Details at level 4 - DSI Test
(e) Details at level 3 - DSI Test
Pressure (Pa)
Time (second)

Wavelet Extracted Features

- Comprised of primitives derived from the normalized energy distributions within the details at level 5, 4, and 3 of the wavelet decomposition.
- Distribution of blast type differ greatly when taken prior to the max pressure, $D_k^- = \frac{1}{N}\sum_{n=t_0}^{t_P}|D_k(n)|$, with respect to distribution after the max blast, $D_k^+ = \frac{1}{M}\sum_{m=t_P}^{t_F}|D_k(m)|$.
- Resulting Ratio $x_{Dk} = \log_{10}\left[\frac{D_k^-}{D_k^+}\right]$
- A5 area is a feature derived from wavelet coefficients at level 5.
- Integrating the magnitude of the area for the coefficients between the start and stop times.
- $A_{5AREA} = \log_{10}\left[\frac{1}{K}\sum_{k=t_0}^{t_F}|A_5(k)|\right]$

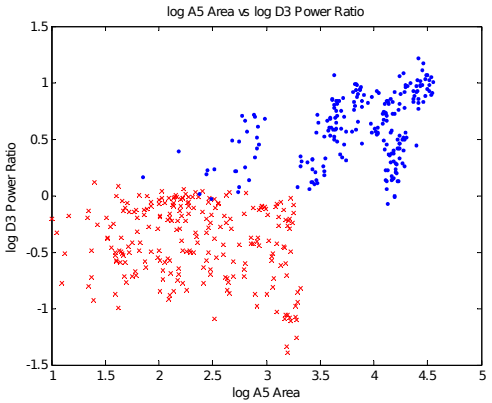
Extracted Features Using DWT

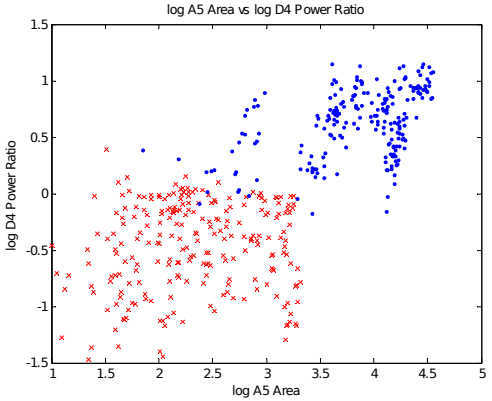

(a) Orignal CB signature @ sensor site 5 - DSI Test
(b) Approximations at level 5 - DSI Test
(c) Details at level 5 - DSI Test
(d) Details at level 4 - DSI Test
(e) Details at level 3 - DSI Test
Pressure (Pa)
Time (Second)
Energy Distribution Prior to Max Blast Pressure
Energy Distribution After Max Blast Pressure


(a) Orignal HE signature @ sensor site 5 - DSI Test
(b) Approximations at level 5 - DSI Test
(c) Details at level 5 - DSI Test
(d) Details at level 4 - DSI Test
(e) Details at level 3 - DSI Test
Pressure (Pa)
Time (Second)
Energy Distribution Prior to Max Blast Pressure
Energy Distribution After Max Blast Pressure

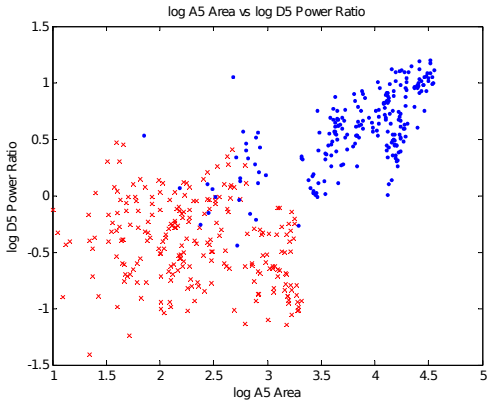
4-tuple Feature Space

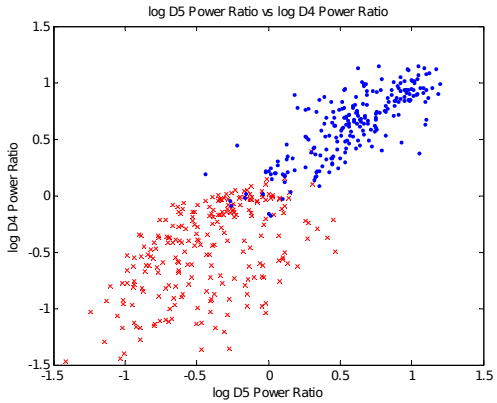
- This energy ratio leads to the discover of 4 features with A5 area that are not amplitude dependent.
- Our n-tuple feature space thus becomes a 4-tuple space, $x^k = [x^k_{D5}, x^k_{D4}, x^k_{D3}, x^k_{5AREA}]$, to be applied for classification.

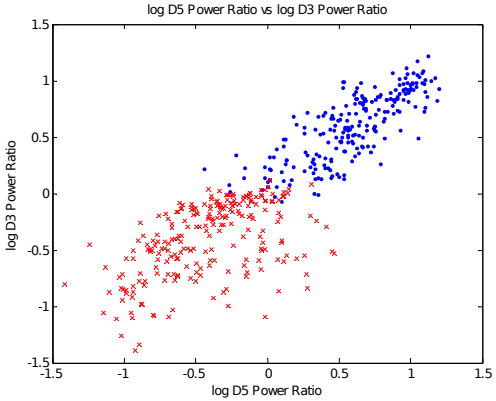


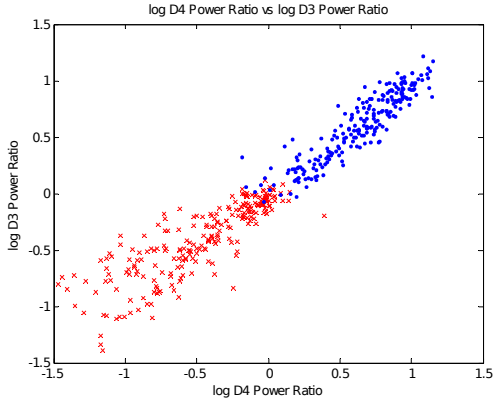


2-D Feature Space Realization

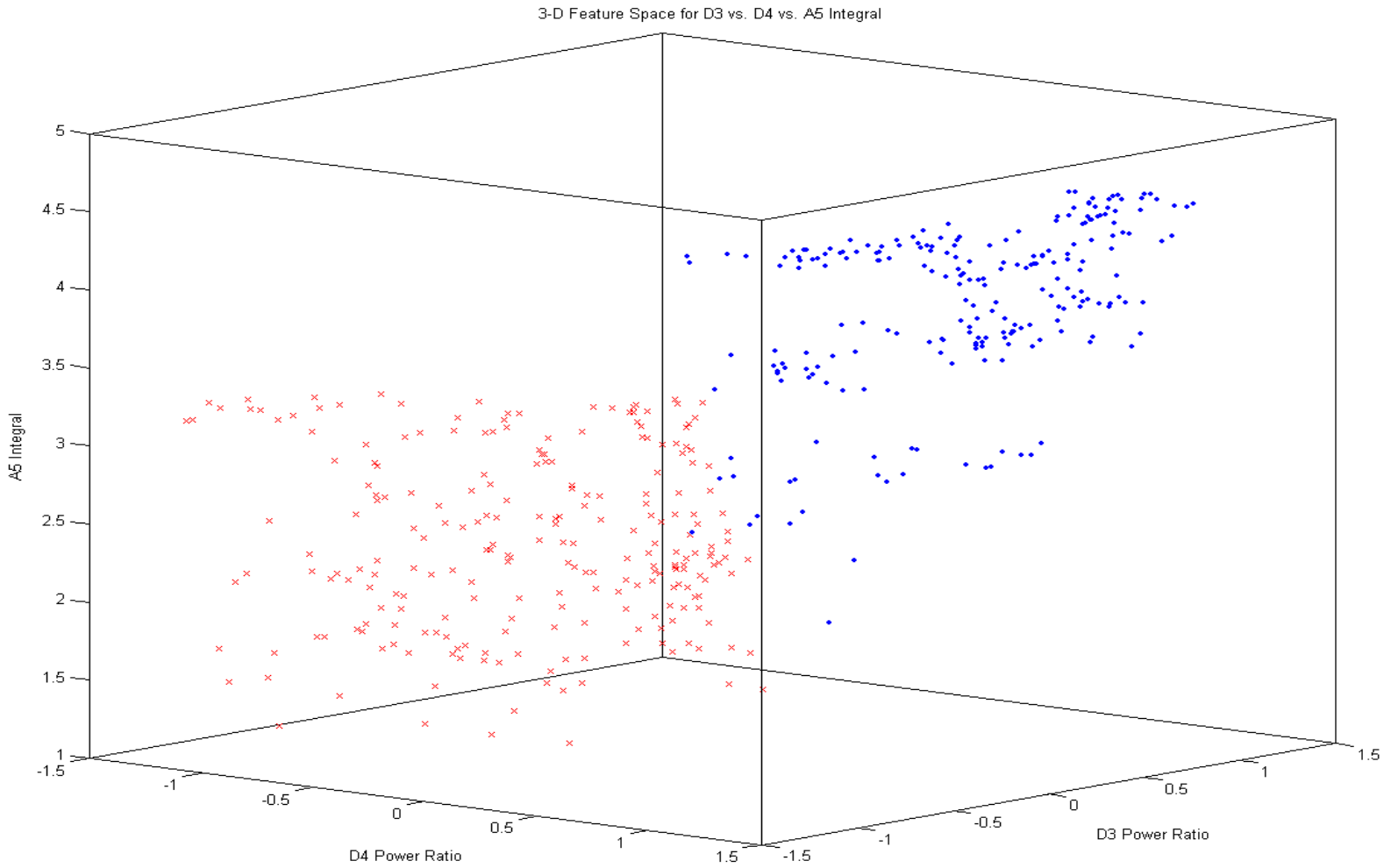






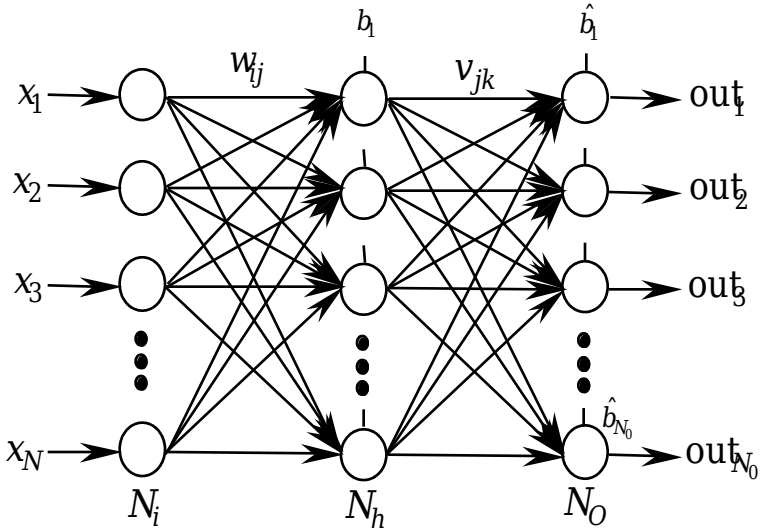


3-D Subspace


3-D Feature Space for D3 vs. D4 vs. A5 Integral
A5 Integral
D4 Power Ratio
D3 Power Ratio

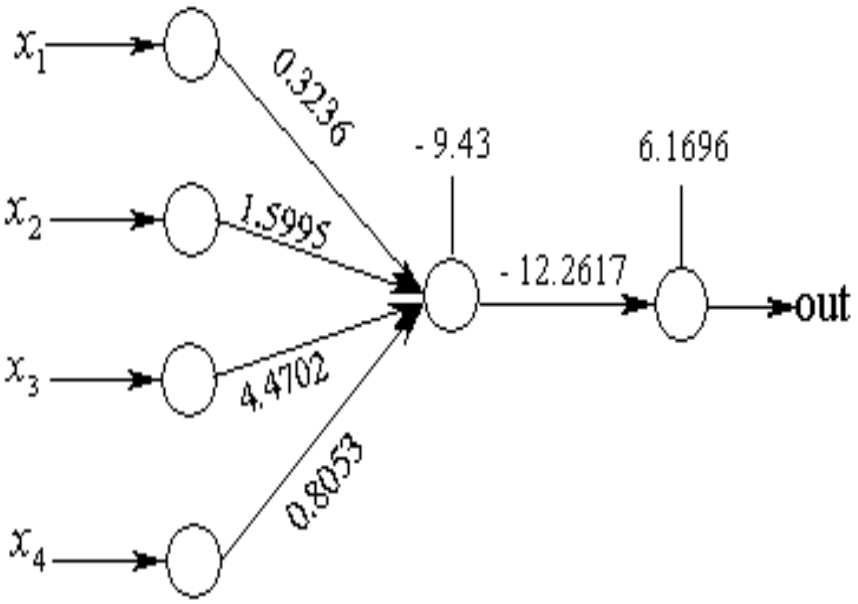
Neural Network

- Realize non-linear discriminant functions and complex decision regions to ensure separability between classes.
- Standard Multilayer Feedforward Neural Network.
- Number of hidden layer neurons depend on complexity of required mapping.



Results of Training Neural Network to DSI Data

- Feature Space created using DWT.
  - 4-tuple feature vector.
  - $x^p = \left| x_{D1}^P \; x_{D2}^P \; x_{D3}^P \; A_{LABEL}^P \right|$
  - 22 randomly selected vectors from 461 signatures.
- Trained Neural Network to trained output data of 0.
  - Single hidden layer neuron.
  - Total error in equation after training is less then 5e-3.
  - Learning rate of 0.1.



Results of HE/CB Discrimination

- Experiment 1
  - Applying a neural network with the weights in the table 1 to DSI data, 99.1% Correct Classification.
- Experiment 2
  - A neural network containing 4 hidden layer neurons trained using entire DSI dataset tested against NCPA dataset, 96.9% Correct Classification.

w_{i1}	w_{i2}	w_{i3}	w_{i4}	v_{j1}
11.6967	0.5343	-0.4958	-2.4991	-13.4966
4.6377	1.2455	3.5569	5.3068	13.3761
4.7023	0.9875	7.3951	8.902	-15.3761
-5.2246	1.481	2.6982	4.1203	-19.6513
-2.8169	1.4847	-18.9732	-23.6088	-14.286

Experiment #	Training Data	Test Data	Classification	Percentage
1	11 CB (DSI)	225 CB (DSI)	225 CB / 0 HE	100%
	11 HE (DSI)	214 HE (DSI)	210 HE / 4 CB	98.10%
2	236 CB (DSI)	166 CB (YPG)	165 CB / 1 HE	99.40%
	225 HE (DSI)	57 HE (YPG)	51 HE / 6 CB	89.50%

Conclusion

- Features extracted facilitate robust classification.
  - Using DWT and Multiresolutional Analysis.
  - Reliable discrimination of CB rounds, 99.7%.
- The features this algorithm is based on go beyond previous amplitude dependent features.
  - Detonation point to disparate sensor exceed 1km.
  - Degradation due to signal attenuation and distortion is nullified.
- Scalable time frequency representation uncovered non-readily detectable features.
  - Subband components remove higher frequency noise features.
  - Isolating the details of higher oscillatory components.

Acknowledgements

- Henry Bass and James Chambers of National Center for Physical Acoustics at the University of Mississippi for providing signature data.
- Chris Reiff from Army Research Lab for his assistance in providing data sets from the DSI test.
- David Sickenberger and Amnon Birenzvige at Edgewood Chemical and Biological Center providing detailed documentation about the test at DSI.